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Applying The Soar Architecture To Model Cognitive Functions In A Kill Chain

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EXECUTIVE SUMMARY

Project Summary

Accurate, relevant and timely combat identification (CID) enables the warfighter to locate and identify critical airborne targets with high precision. The current CID processes include the use of Naval and Joint combinations of platforms, sensors, networks and decision makers. There are diversified doctrines, rules of engagements, knowledge repositories and expert systems used in the current process to address the complexity of decision making challenges. However, the process is still very manual and decision makers can experience cognitive overload.

Soar is a software and architecture system that models complex reasoning, cognitive functions and decision making. It can be used to model cognitive decisions for tactical warfare such as engagement decisions in a kill chain. The cognitive functions include decision making, sensor fusion, analytic processes and workflow. We used Soar to aid in the in the CID decision making process.

We used Soar and specifically the reinforcement learning (RL) method for the cognitive functions of the CID decision making process. For this focus, the problem space has been characterized. Soar production rule pseudocodes, and the procedural knowledge and basis for reasoning were formulated in the project. We also produced a use case, a prototype and a student thesis.

Background

Soar is cognitive architecture and software system that has been developed by the University of Michigan (Soar, 2017) to model complex reasoning, cognitive functions and decision making. Soar is continually being updated and has recently added reinforcement learning. The Navy's current methods for tactical airspace combat identification are largely manual. The process of CID involves diversified doctrines, rules of engagements, knowledge repositories, and expert systems to some degree. Decision makers such as Tactical Action Officers (TAOs) and Mission Commanders (MCs) can experience cognitive overload because of the demanding process of CID. For example, the current CID process requires complex decision making capabilities from the TAOs/MCs in order to conduct the CID process which includes evaluating traditional sensor measures, indications and assessing data driven models (e.g., rules such as Rules of Engagement (ROE), expert systems, and analytic models). These models may be developed historically or separately from legacy sources. These models may not be complete, can have low confidence levels, or even contain conflicting and wrong data. Furthermore, advanced Big Data, Deep Analytics, Machine Learning (ML) and/or Artificial Intelligence (AI) can also result in analytic models (e.g., new threatening behavior models fused from massive data sources) with various confidence levels. These new models need to be incorporated and adapted to a holistic CID decision making process.

The core questions for the project in the past year are the following:

- Can Soar, incorporated in a CID process, learn and better use the existing knowledge models for CID cognitive functions, timely and automatic decision making?
- Can Soar, incorporated in a CID process, learn from the feedback of human operators?

Soar is especially suitable for DoD applications because it can accept and use knowledge systems including English-language based rules as well as Deep Analytics or Smart Data. Therefore, it has the potential to learn and discover the optimal combinations of existing knowledge models for CID and can generate ML/AI that can automate and speed up the complex decision making for CID. Ultimately this has the potential to reduce the cognitive and mental burden on human CID operators.

We compared Soar with commercial AI systems such as DeepMind (DeepMind, 2017), developed by Google, which is a system that taught itself to play the games, Breakout (Breakout, 2017) and Go (Go, 2017). Soar-RL is different from DeepMind-RL. DeepMind-RL is learning from low-level data (e.g. pixels for games) and uses Deep Learning, e.g., CNN (Caffe, 2017), for function approximation of the value function. Soar is –based on more traditional AI, which makes it easier to adapt to symbolic/rule-based problems like in the kill chain and CID applications. Furthermore, for the CID application, a model is needed that looks at a representation of the common operating picture (COP) such as a Common Tactical Air Picture (CTAP) and bases its decisions on this knowledge. The model must provide visibility of the objects in the COP and their properties. The model must learn. Soar satisfies these requirements. It is also a requirement for human operators to have insight into how decisions are made for validation. An advanced AI model such as Hidden Markov Models (HMM, 2017) does not perform the work; Soar can do it. One also wants to plug the cognitive models into a simulation to assess system of systems effectiveness. The Naval Simulation System (NSS) and Soar were selected after evaluating alternatives for Navy.

Findings and Conclusions

In the past, the NPS team worked with a thesis student, who was an experienced E-2 Mission Commander (MC), who demonstrated the feasibility of this idea and built a prototype Soar-RL model using simple three rules for a CID use case for this project. From the NPS prototype results, after a period of time for a learning phase, the Soar prototype allows the operator to gradually put a trained agent into the operational phase. The correct decision rate (i.e., deciding hostile or non-hostile for unknown airborne object) went from 62.5% to 87.5% with a statistical significance p-value<=0.04. The results are documented in the NPS thesis (Mooren, 2017).

In conclusion, the team is using the Soar-RL method, the team has characterized the problem space and has developed Soar production rule pseudocode as the procedural knowledge and basis for reasoning. We proved, in a small scale, that Soar can incorporate existing knowledge as production rules into long-term and short-term memories for decision making. The Soar-RL can improve, validate, simplify and even generate new rules based on feedback from external elements (e.g., human operators or other training data). Specifically,

- We showed it is feasible that Soar-RL can learn and better use the existing knowledge models for CID cognitive functions, timely and automatic decision making.
- We also demonstrated that it is feasible that Soar-RL incorporated in a combat system can learn from the feedback of human operators. The trained Soar agent can be used to adapt to the future situations, perhaps making decisions like human operators and reduce the cognitive burdens of human operators.

Recommendations for Further Research

The following are a few of future research tasks we recommend based on the results of this study:

- This continuation of the cognitive modeling will build on the prior effort that introduced Soar-RL. Future work will expand on the sensory and data analytics input and experience of the cognitive model. A prototype will be refined that uses the Soar cognitive architecture. The Soar model will be added to the simulations to be informed by wargames for mission planners. For example, recommendations are to incorporate the Soar prototype into the Naval Simulation System (NSS) and the Warfighting Impact by Simulated Decision Makers (WISDM).

- It might be feasible to examine ML/AI in Soar-RL for the cross-validation Deep Analytic models. It might be feasible to examine ML/AI in Soar-RL to learn from the delayed ground truth after actions taken.

- The models could not only automate many current manual CID processes but also have the potential to be applied in other DoD applications of decision making that require overwhelming cognitive functions of experienced warfighters. For example, a need from the Spectrum Technology Advanced Research (STAR) LNAVSEA NSWC Crane is to use Soar to learn new rules.

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